International Journal of Engineering Education Vol. 31, No. 4, pp. 1081–1091, 2015
Printed in Great Britain
0949-149X/91 $3.00+0.00

Mobile Learning Adoption: An Empirical Investigation for Engineering Education*

YU HUAN[1], XUEPING LI[1], MEHMET AYDENIZ[2] and TAMI WYATT[3]
[1]Department of Industrial and Systems Engineering, University of Tennessee, Knoxville, TN 37996, USA. E-mail: Xueping.Li@utk.edu
[2] Department of Theory and Practice in Teacher Education, University of Tennessee, Knoxville, TN 37996. USA.
[3] Health Information Technology and Simulation Lab, University of Tennessee, Knoxville, TN 37996, USA.

The emergence of mobile learning or m-Learning indicates a new opportunity for the education industry. Yet, there is a lack of a comprehensive understanding about the factors that influence its effective adoption. Further, it is unclear how to implement m-Learning that incorporate all stakeholders' perspectives. Built on Unified Theory of Acceptance and Use of Technology (UTAUT), this paper presents an extended adoption model and an empirical evaluation using data collected from a survey of engineering students ($N = 377$). The structural equation modeling technique is used to evaluate the causal model and confirmatory factor analysis is performed to examine the reliability and validity of the measurement model. Our findings indicate that performance expectancy, attainment value, self-management of learning, ubiquity, service quality, and perceived enjoyment significantly affected m-Learning adoption intention. The implication of this study to educators, system designers, and university administrators is discussed.

Keywords: engineering education; mobile Learning (m-Learning); technology adoption; Unified Theory of Acceptance and Use of Technology (UTAUT)

1. Introduction

Mobile technology is essential to and positively impacts educational systems; it plays a significant supplemental role within formal education [1]. Ubiquitous computing and mobile communication changes students' interactions and learning behaviours individually and with others in society. Mobile learning or m-Learning, defined as "*learning across multiple contexts, through social and content interactions, using personal electronic devices*" [2], is believed to be the next frontier studied because of the potential to enhancing learning and education systems for students and universities. With m-Learning and mobile devices, the learning can take place in a variety of contexts, within and beyond traditional learning environments.

As mobile technology becomes increasingly viable and less expensive, it has resulted in a wide range of mobile devices available for use in higher education. Moreover, the educational needs have resulted in the development of educational applications that exploit the ubiquitous connectivity and high levels of portability [3–5]. For example, the US government is seeking to reduce costs by encouraging schools to transition from paper-based to digital textbooks within next five years [6]. The same mobile devices that host digital textbooks can also run mobile device applications (e.g. apps) that become study aids accessible to students from virtually anywhere [7].

While there is a growing interest in m-Learning from education industry, the complexities with adoption of m-Learning from both learner's and educational institution's perspectives seem largely unsolved [8]. The availability of various mobile devices for students does not guarantee their use for learning purposes; implementing m-Learning in higher education is still challenging because of social, cultural, and organizational factors [8, 9]. Thus, there appears to be an urgent need to understand factors influencing students' intention to adopt m-Learning. This is important because many schools are motivated to invest significant resources into integration of mobile technologies into their instruction. Moreover, the enrolment in engineering and the number of students who successfully graduate with an engineering degree is declining [10]. With an increasing demand for well-educated engineers who are proficient in science, technology, engineering, and mathematics (STEM), the adoption of mobile technology in education practices seem to be one of the solutions for creating a compelling and yet effective learning experience for the students.

While the theoretical argument for the integration of mobile technologies into engineering education to increase student interest and learning seems compelling, the literature lacks empirical evidence in support of this argument. Only few studies aimed to implement m-Learning systems in the engineering education context (e.g. [11, 12]); most of studies primarily focused on language acquisition [13]. Moreover, the issues of technology acceptance and adoption have been largely overlooked among those studies. Recognizing this gap in the literature,

* Accepted 18 February 2015.

this study aimed to identify the factors that impacted engineering college students' adoption of m-Learning using the Unified Theory of Acceptance and Use of Technology (UTAUT) [14] as the theoretical framework. The findings of this study have significant implications for higher education institutions as well as k-12 institutions that aim to integrate m-Learning into their curriculum.

The remaining paper is organized as follows. First, we propose the research model as the basis of this empirical evaluation. Next, we discuss and describe the methodology applied in this study including variables and their measurement. Last, we present the results of data analysis followed by a discussion of the findings, important implications, and conclusions.

2. Research model and hypotheses development

2.1 Theoretical background

The Unified Theory of Acceptance and Use of Technology (UTAUT) was originally proposed by Venkatesh et al. [14] and was based on the foundations of the following: (1) Theory of Reasoned Action (TRA), (2) Technology Acceptance Model (TAM), (3) Motivational Model (MM), (4) Theory of Planned Behaviour (TPB), (5) Combined Technology Acceptance Model and Theory of Planned Behaviour (C-TAM-TPB), (6) Model of PC Utilization (MPCU), (7) Innovation Diffusion Theory (IDT), and (8) Social Cognitive Theory (SCT). The UTAUT theory seeks to explain intentions to use an information system and subsequent usage behaviour. The theory holds that key constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of information system usage intention, usage behaviour, gender, age, experience, and voluntariness of use moderate the impact of the four key constructs on usage intention and behaviour [14]. The original UTAUT model is presented in Fig. 1.

M-Learning emerges as a new education practice generally used in a social context, and thus the fundamental constructs of UTAUT may not fully reflect the unique influence of m-Learning and the factors that may alter user adoption and usage of technology. Additionally, UTAUT is a relatively new framework and needs further research to replicate findings and validate its measures and robustness [15]. Although UTAUT has been validated in subsequent information system research, there are still unexamined theory components that may fall within the 30% unexplained acceptance and account for invariance of the UTAUT scales across different cultures, populations, and novel applications [14, 16, 17]. Furthermore, UTAUT does not include individual factors like perceived playfulness and self-motivation that may help explain information system acceptance and use of mobile devices [18]. Therefore, proper extension and modifications of the original model are necessary in order to integrate the variables reflecting the unique characteristics of m-Learning.

2.2 Research model and hypotheses

As aforementioned, the UTAUT model needs proper modification to integrate mobile technology-specific features into the traditional adoption

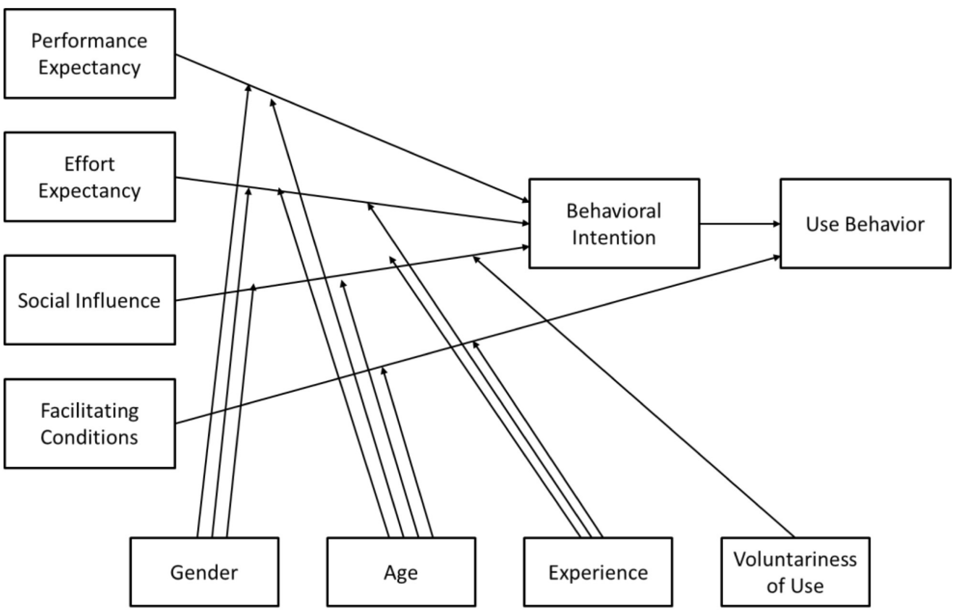

Fig. 1. The UTAUT model [14].

model. Therefore, the proposed research model includes six newly-added variables in addition to four key variables in traditional the UTAUT model. Fig. 2 presents the UTAUT in an m-Learning context. Each key variable is further explained next.

Performance expectancy is defined as the degree to which an individual believes that using a particular system will help him or her to attain gains in job performance [14]. A positive relationship between performance expectancy and behavioural intention has not been demonstrated [14]. Hence, adapting performance expectancy to the context of m-Learning suggests that individuals will find m-Learning useful due to convenient access to information without the restriction on physical locations and time.

Effort expectancy is considered as the degree of ease associated with the use of the particular information system [14]. To the extent that promoted effort expectancy leads to improved performance, previous studies indicated that effort expectancy had a direct effect on performance expectancy and intention to use m-Learning [19]. Therefore, effort expectancy is included in the study.

Social influence is defined as the degree to which an individual perceives that important persons believe he or she should use the new system. Previous literature suggested social influence was a strong predictor of behavioural intention in shaping an individual's intention to use a new technology system [14, 20, 21]. In the context of m-Learning, it indicates that social influence will strongly affect students' intention to accept and use mobile devices for academic purposes. As a learner's decision is also influenced by others [22, 23], it is rational to include social influence for evaluation.

Facilitating conditions refer to the availability of resources needed to engage in behaviours, such as time or money. Literature suggested that facilitating conditions had a significantly positive effect on an individual's use of an information system [24]. Concannon et al. [25] also emphasized the importance of providing students with guidance and technical support to facilitate engagement with learning technologies. In the context of m-Learning, learner's satisfaction and decisions are affected by the perception of the support from learning material providers, functionality of systems, and so forth. Hence, facilitating conditions appear to be an important factor influencing the user's intention and thus behaviour.

Self-efficacy refers to the personal belief in one's own ability to complete tasks and reach goals [26]. In the context of m-Learning, it indicates an individual's perception of his or her capability to use a mobile device to engage in learning tasks, locate and manipulate information, and communicate and collaborate using social technologies. Hence, self-efficacy is also included in the study.

Ubiquity is the most significant and advantageous

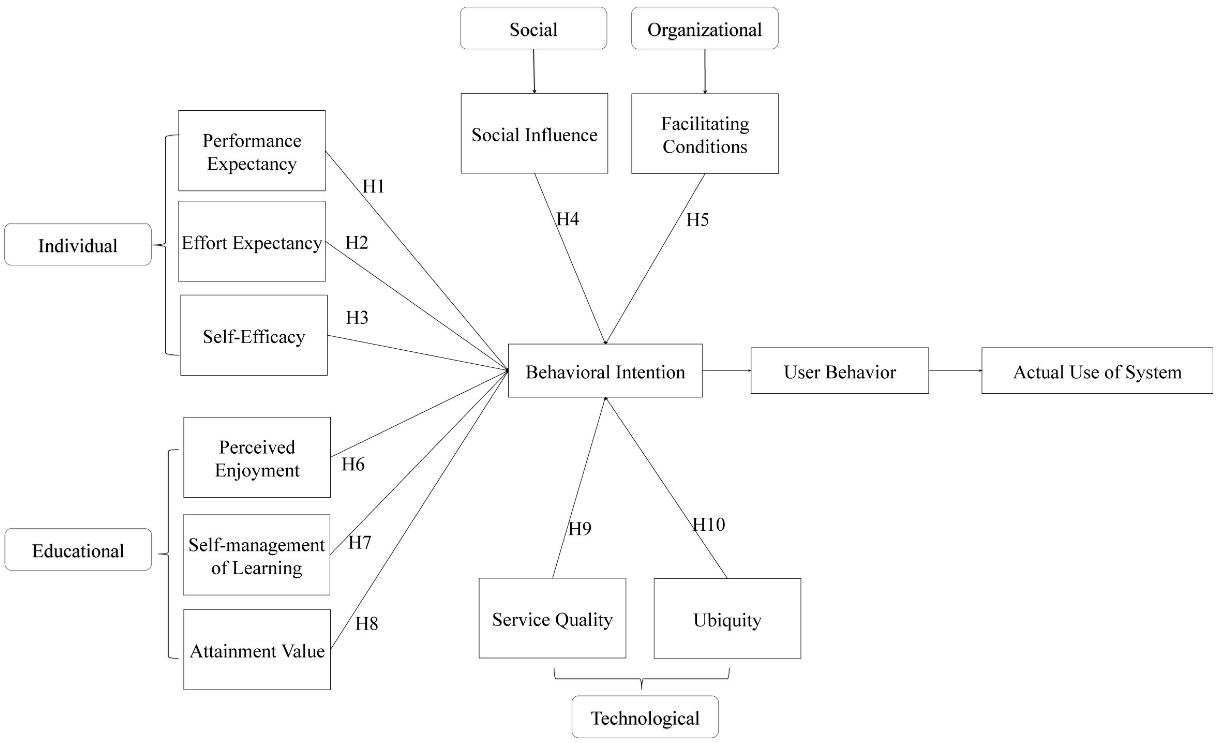

Fig. 2. UTAUT for m-Learning.

feature of m-Learning compared to traditional education approaches [27]. Previous studies suggested importance of ubiquity in affecting user's decision to adopt particular mobile services [18, 28, 29], and therefore, it is necessary to involve ubiquity in the study.

Service quality refers to reliability and content quality. Daft and Lengel [30] suggested that accuracy, reliability, and quality of information exchanged across a medium were critical to the effectiveness. In the context of m-Learning, content refers to the information, resources, and functions that are offered via m-Learning services. Such content should be constructed logically to help learners find information and incorporate features such as accuracy, timeliness, relevance, and flexible presentation [31]. A reliable m-Learning system can ensure the effectiveness of m-Learning, and therefore, service quality is included in the study.

Attainment value, defined by [32], is the personal importance of performing with regard to self-schema and core personal values, such as achievement. According to [33], tasks will have higher attainment value to the extent they allow the individual to confirm salient aspects of the learner's self-schema. Chiu and Wang [34] indicated a positive relationship between attainment value and continuance intention from a perspective of technology-enhanced learning. Accordingly, the learner's decision regarding the use of m-Learning may be influenced as well by perceived attainment value. Thus, it is introduced in the study.

Self-management of learning refers to the extent to which an individual perceives that he or she is self-disciplined and enables one to engage in autonomous learning [35]. Successful learning is derived from learner's control of the learning activity, exploration and experimenting, asking questions, and engaging in collaborative argumentation [36]. In the context of m-Learning, students need to manage their own learning as they are separated from faculty, peers, and institutional support. This autonomy entails an increased need for skills in critical thinking, identifying learning needs, and locating and evaluating resources [37–39]. As a result, self-management of learning is included in the study.

Perceived enjoyment refers to an individual's performance or engagement in an activity due to his or her interest in the activity [40]. Some studies have shown that perceived enjoyment is a significant determinant of the behavioural intention to use m-Learning and mobile services [29, 39, 41]. It is necessary to make learning activities more enjoyable to promote learner's acceptance and use of m-Learning. Therefore, perceived enjoyment is included in the study.

The proposed research model depicted in Fig. 2 considers an m-Learning initiative from organizational, technological, educational, social, and individual perspectives in a university environment. It is comprehensive and incorporates the factors that may impact students' adoption of m-Learning services found throughout the literature. Based on the research model, the following hypotheses are tested in this study.

- Hypothesis 1 (H1): Performance expectancy (PE) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 2 (H2): Effort expectancy (EE) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 3 (H3): Self-efficacy (SE) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 4 (H4): Social influence (SI) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 5 (H5): Facilitating conditions (FC) are positively related to behaviour intention to use m-Learning.
- Hypothesis 6 (H6): Perceived enjoyment (PEn) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 7 (H7): Self-management of learning (SML) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 8 (H8): Attainment value (AV) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 9 (H9): Ubiquity (Ubi) is positively related to behaviour intention (BI) to use m-Learning.
- Hypothesis 10 (H10): Service quality (SQ) is positively related to behaviour intention (BI) to use m-Learning.

3. Methodology

3.1 Study context and participants

The sample in this study was 3222 students enrolled in the college of engineering during the 2013 spring semester at a university in the south-eastern part of the United States. A total of 377 students responded to the survey. There were no missing data in this study since each question required an answer. Of all respondents, 28.9% were female, and 71.1% were male. The college level of the respondents was: 12.2% freshmen, 16.2% sophomores, 18.0% juniors, 28.7% seniors, and 24.9% graduate level students. Approximately 81% of students reported having used mobile devices for learning purposes. Eighty-two percent of the respondents owned a Smart-

Table 1. Sample demographic profile

	Number	Percent (%)
Gender		
Female	109	28.9
Male	268	71.1
Age		
< 18	1	0.3
18-22	229	60.7
23-26	75	19.9
>26	72	19.1
College level		
Freshman	46	12.2
Sophomore	61	16.2
Junior	68	18.0
Senior	108	28.7
Graduate	94	24.9
Prior m-Learning experience		
Yes	305	80.9
No	72	19.1
Mobile device ownership		
Smartphone	308	81.7
PDA	8	2.1
Tablet	157	41.7
MP3 or similar device	203	53.8
No devices	6	1.6

Table 2. Instrument measurement

Construct	Reliability (α)	AVE
Behaviour intention	0.899	0.690
Performance expectancy	0.898	0.688
Effort expectancy	0.882	0.651
Self-efficacy	0.701	0.537
Perceived enjoyment	0.799	0.665
Social influence	0.822	0.699
Facilitating condition	0.842	0.728
Self-management of learning	0.855	0.663
Ubiquity	0.743	0.592
Attainment value	0.921	0.854
Service quality	0.913	0.724

phone. Only 1.6 % of respondents did not own any type of mobile device. Table 1 presents the demographic profile of the sample.

3.2 Data collection

The data collection instrument was adapted from previous literature and studies in different contexts. It consisted of 32 five-point likert-scale items, ranging from completely disagree to completely agree. Higher scores on this instrument indicated more positive perceptions of m-Learning. To avoid confusion and misunderstanding, the names of each construct were excluded in the survey. The instrument was deployed and administered online. The consent form and URL link to the survey was sent to students via email. The submission of the survey indicated their consent. To maximize the return rate, two follow-up emails were sent after the initial recruitment email.

3.3 Model assessment and hypotheses testing

The data obtained were tested for reliability and validity using confirmatory factor analysis (CFA) with maximum likelihood method in AMOS20. This step was used to test if the empirical data conformed to the presumed model. The reliability was evidenced by internal consistency reliability (Cronbach's alpha) and average extracted variance (AVE). A commonly used threshold value for internal consistency reliability is 0.70 [42]. For the latter, guidelines recommend the average variance extracted value should exceed 0.50 for a construct [42]. All measures in Table 2 exceeded these recommended values. The standardized loading values in Table A.1 exceeded 0.7, thereby demonstrating convergent validity at the item level [43]. Discriminant validity was confirmed by examining correlations among the constructs. As a common threshold, a correlation of 0.85 or higher indicates poor discriminant validity [44]. The results in Table 3 suggested an adequate discriminant validity of the measurement. The goodness-of-fit test presented a good fit between the data and the proposed model. The model fit indices in Table 4 satisfied the recommendations by [45, 46].

Table 5 gives a summary of testing results including path coefficients and variance explained. The results were obtained by structural equation modelling (SEM) in AMOS20. The advantage of SEM is that it considers both the evaluation of the measurement model and the estimation of the structural coefficient at the same time [42]. Based on the results, effort expectancy, self-efficacy, facilitating

Table 3. A correlation matrix between constructs

	BI	PE	EE	SE	PEn	SI	FC	SML	Ubi	AV	SQ
BI	1.000										
PE	0.815	1.000									
EE	0.628	0.628	1.000								
SE	0.413	0.432	0.256	1.000							
PEn	0.813	0.793	0.649	0.400	1.000						
SI	0.588	0.538	0.427	0.476	0.550	1.000					
FC	0.535	0.484	0.349	0.657	0.538	0.617	1.000				
SML	0.766	0.769	0.579	0.461	0.780	0.645	0.565	1.000			
Ubi	0.782	0.736	0.581	0.468	0.746	0.646	0.615	0.813	1.000		
AV	0.607	0.576	0.376	0.321	0.647	0.490	0.415	0.648	0.500	1.000	
SQ	0.381	0.183	0.258	0.211	0.252	0.354	0.266	0.215	0.401	0.050	1.000

Table 4. Model fit indices

Indices	χ^2/df	GFI	AGFI	NFI	IFI	TLI	CFI	RMSEA
Obtained Value	1.614	0.91	0.881	0.929	0.972	0.965	0.971	0.04
Recommended Value	< 3	> 0.9	> 0.8	> 0.9	> 0.9	> 0.9	> 0.9	< 0.05

Table 5. Hypothesis testing results

Hypothesis	Support	Path coefficients	*P*-value
H1: Performance expectancy (PE) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.367	<0.001
H2: Effort expectancy (EE) is positively related to behaviour intention (BI) to use m-Learning.	N	0.005	>0.05
H3: Self-efficacy (SE) is positively related to behaviour intention (BI) to use m-Learning.	N	–0.053	>0.05
H4: Social influence (SI) is positively related to behaviour intention (BI) to use m-Learning.	N	–0.012	>0.05
H5: Facilitating conditions (FC) are positively related to behavior intention to use m-Learning.	N	0.030	>0.05
H6: Perceived enjoyment (PEn) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.277	<0.001
H7: Self-management of learning (SML) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.136	<0.001
H8: Attainment value (AV) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.118	<0.001
H9: Ubiquity (Ubi) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.258	<0.001
H10: Service quality (SQ) is positively related to behaviour intention (BI) to use m-Learning.	Y	0.141	<0.001
R^2=0.879			

conditions and social influence had no significant influence on behaviour intention to use mobile devices for learning, indicating that hypotheses 2–5 were not supported. Consistent with the hypotheses, performance expectancy, ubiquity, attainment value, service quality, self-management of learning, and perceived enjoyment had significant influence on behaviour intention, indicating that hypotheses 1 and 6–10 were supported. In total, the proposed adoption model explained 87.9% of the variances of adoption intention.

Furthermore, t-tests and ANOVA tests were conducted to determine significant differences in intention to adopt m-Learning between student groups. The t-tests revealed significant difference on behaviour intention between females and males (t = –2.096, p < 0.05) and between students with m-Learning experience and those who did not (t = 6.182, p < 0.001). There was no significant difference on intention to use mobile devices for learning regardless of students' age or college level based on ANOVA results (F =1.043, p > 0.05 for age groups; F = 2.112, p > 0.05 for college level groups). However, the students who owned a Smartphone or a tablet showed significant difference on intention to adopt m-Learning from those who did not own any of these devices (t = –3.89, p < 0.001 for Smartphone ownership; t = –3.462, p < 0.001 for tablet ownership). Further, there was no significant difference with respect to ownership of other types of mobile devices.

4. Discussion and implication

The results specified six significant motivators of m-Learning adoption, which are performance expectancy, attainment value, ubiquity, service quality, self-management of learning, and perceived enjoyment. Of all these factors, performance expectancy was the strongest determinant of user intention. It is therefore believed that the more students perceive m-Learning is useful for learning and improves their performance, the more likely they will engage in it. In order to increase performance expectancy, educators may take advantage of value-adding characteristics of m-Learning. For example, educators can encourage students to use of mobile devices to get timely knowledge, make quick responses or decisions and emphasize learning productivity. To facilitate the adoption of m-Learning, educators and universities can also offer students m-Learning courses that address their long-term benefits, such as academic life development.

The second significant factor found in this study was perceived enjoyment. Results suggest the more students enjoy m-Learning, the more they will be motivated to engage in m-Learning activities. Given m-Learning is fully voluntary and target user groups have diversified backgrounds, it is crucial to make systems interactive and enjoyable for students to use it. To promote m-Learning, educators and system designers should consider designing experimental activities that relate resources to students' experience, knowledge level, interests, and needs. In this way, students may feel more absorbed in the task and in control of the learning process, which may help them experience perceived playfulness and, in turn, increase system users.

Ubiquity and service quality also have significant influence on students' intention to adopt m-Learning. Results in this study suggest a positive connection between ubiquitous access to learning community and students' intention to adopt m-Learning. Also, currency, accuracy, and understandability of content are essential to students. Thus, the university and educational practitioners must address these issues in their m-Learning implementation so that these aspects do not prohibit students from using it. Furthermore, system designers should attend to content presentation and communication standards, thus making learning contents portable to diverse types of mobile devices. Meanwhile, systems designers should also focus on functions that provide up-to-date content that fits users' needs giving them control of their learning progress and recording their performance. Consequently, students may perceive that m-Learning is more personal and flexible, thereby facilitating the m-Learning adoption.

Previous research found that learners more likely engaged in m-Learning activities if they had a higher level of autonomous learning skills [35]. Consistent with the literature, the results in this study indicate that self-management of learning is a significant determinant of students' intention to use m-Learning. This finding can help pedagogical policy makers and instructors design corresponding curricula that inspire and boost students' capability of self-management of learning. In addition, educators should diligently deliver these curriculums to cultivate students' habit of continuous self-learning and life-long learning.

Attainment value measures personal importance of doing well with regard to self-schema and core personal values, such as achievement [32]. The results in this study indicate that attainment value is a significant determinant of students' intention to use mobile devices for learning. For educators and university administrators, it is important to cultivate students' positive attitudes that are congruent with their values, commitment, and readiness for using m-Learning.

Effort expectancy and self-efficacy have no significant influence on intention to use m-Learning based on these results. This may be due to the students' familiarity with mobile devices, which is seen in demographic data that 98.4% of students owned mobile devices. Thus, using a mobile device appears to be routine for many students and doesn't confine their capabilities of performing learning tasks. Students may perceive using mobile devices for learning as similar to using it for other tasks. This finding indicates that, to some extent, technological restrictions do not raise significant usability problems that inhibit m-Learning adoption. It may be largely due to the availability of large screen mobile devices (e.g. iPad, Samsung Galaxy Note) and efforts to design m-Learning systems and materials suitable for mobile usage. As a result, the feeling of ease of use was broadly perceived among students, which led to insignificance of effort expectancy and self-efficacy in the study.

Contrary to the literature (e.g. [14, 24]), the results exclude facilitating conditions and social influence as the determinants of students' intention to use m-Learning. This may pertain to the study context. M-Learning is a new trend at the university where the study took place. The office of information technology of the university only initiated an "*Innovative Mobile Learning (mLearning) Project*". However, it was not a campus-wide project, and only a few classes and faculties in the college of engineering participated in this project. The results may indicate, to some extent, students' lack of awareness of university commitment to m-Learning. The m-Learning services cannot be simply provided to students without support. Involvement of all stakeholders in the phases of deployment, such as introducing students the benefits of m-Learning, encouraging faculties to use mobile devices in classes, is also important. Students may consider the level of support available for a new system (e.g. an m-Learning system) as demonstrating institutional expectations for their usage of the system [14]. Faculties can also consider providing their courses on iTunes U or other m-Learning management systems and refer students to these platforms for academic learning.

During the survey, the participants were also asked to indicate what learning resources and activities they would prefer for m-Learning; results are presented in Fig. 3 and Fig. 4. Although m-Learning is capable of offering a new pedagogical approach, students' preferences were not sophisticated. Access to lecture PPT slides and sharing information (e.g. email) ranked the highest interests respectively. It may suggest that providing more mobile friendly course information could be the first step to implement m-Learning. Nonetheless, universities and educators need to explore more instructional models that employ unique capacities of mobile devices. Sixty-nine percent of students expressed interests in educational mobile applications. This presents an opportunity for educational system designers.

5. Limitations and future research

Though this study has employed rigorous procedures, there are some limitations that can be addressed in future research. First, findings and their implications discussed in this study were based on one study that examined a particular university. Future research can include more universities to validate and replicate research findings. Second, this study was cross-sectional, which mea-

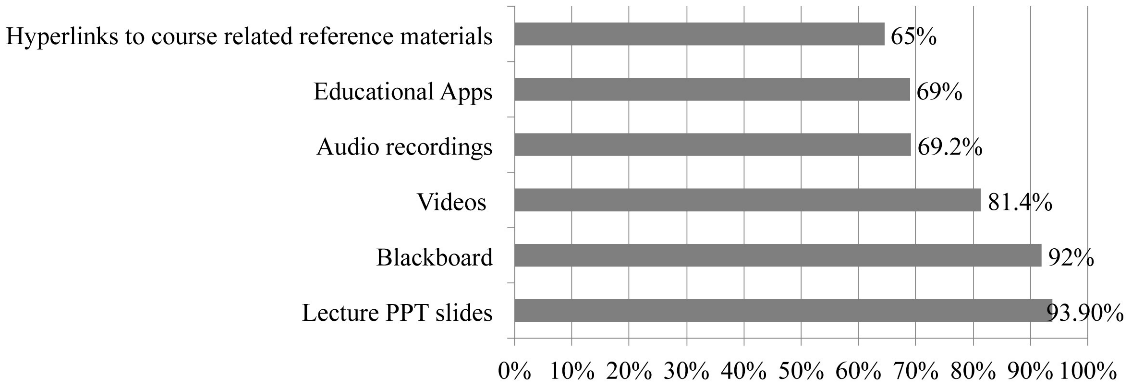

Fig. 3. Students' preference to learning resources for m-Learning. It illustrates the top six learning resources that students would prefer for m-Learning.

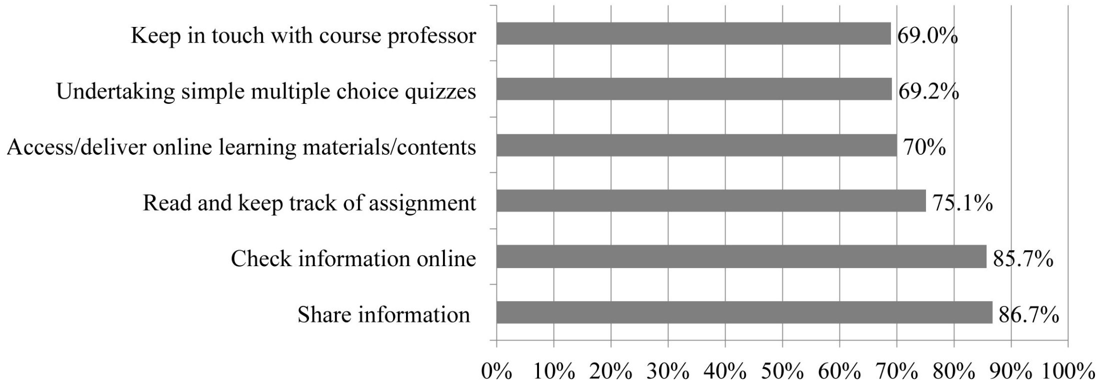

Fig. 4. Students' preference to learning activities for m-Learning. It illustrates the top six learning activities that students would prefer for m-Learning.

sured perceptions and intentions at a single point in time. However, perceptions change over time as individuals gain experience [14]. Future research may include longitudinal data for evaluation. Third, this study relied on students' self-reported data; thus, there may be a common method bias for some of the results. Fourth, future studies can also examine the linkage between students' intention to use m-Learning and actual usage when institutional m-Learning applications have been implemented. Last, this study mainly investigated students' intention to use mobile devices for learning. In the future, research can incorporate faculties' perceptions, which may shed more light on instructional design and pedagogical policy of m-Learning.

6. Conclusion

Mobile learning implementation is a complex technical and culture challenge for education systems. Universities could be benefit from understanding the determinants of m-Learning adoption thus to overcome such a challenge. Serving this purpose, the study demonstrated factors that impacted students' adoption of m-Learning through a user acceptance model with a few newly investigated variables. We found that performance expectancy, attainment value, ubiquity, service quality, self-management of learning, and perceived enjoyment were key factors affecting the adoption of m-Learning. The results showed that 87.9% of intention to adopt m-Learning was explained by the components in the extended Unified Theory of Acceptance and Use of Technology (UTAUT) model. This study added new understanding and knowledge to technology acceptance theory and m-Learning. Decision-makers in universities could also manipulate those factors to achieve an organizational and pedagogical success in an m-Learning adoption and implementation.

References

1. Educating the Net generation, http://net.educause.edu/ir/library/pdf/pub7101.pdf, Accessed June 30, 2013.
2. H. Crompton, A historical overview of mobile learning: Toward learner-centered education, in Z. L. Berge and L. Y. Muilenburg (eds.), *Handbook of mobile learning*, Routledge, Florence, KY, 2013, pp. 3–14.
3. T. Cochrane and R. Bateman, Smartphones give you wings: Pedagogical affordances of mobile web 2.0, *Australasian Journal of Educational Technology*, **26**(1), 2010, pp. 1–14.
4. S. Hall and E. Anderson, Operating systems for mobile computing, *Journal of Computing Sciences in Colleges*, **25**(2), 2009, pp. 64–71.

5. C. Schmitt, J. Rodriguez and R. Clothey, Education in motion: From iPod to iPhone, *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications*, Chesapeske, VA, 2009, pp. 4308–4313.
6. Obama administration's challenge to schools: Embrace digital textbooks within 5 years, http://www.huffingtonpost.com/2012/02/01/challenge-to-schools-embr_n_1248196.html, Accessed July 15, 2013.
7. Smartphones on campus: The search for 'killer' apps, http://chronicle.com/article/Smartphones-on-Campus-the/127397, Accessed July 15, 2013.
8. J. R. Corbeil and M. E. Valdes-Corbeil, Are you ready for mobile learning?, *Educause Quarterly*, **30**(2), 2007, pp. 51–58.
9. J. Traxler, Sustaining mobile learning and its institutions, *International Journal of Mobile and Blended Learning*, **2**(4), 2010, pp. 58–65.
10. National Science Foundation, http://www.nsf.gov/statistics/seind12/pdf/c02.pdf, Accessed July 15, 2013.
11. A. Istanbullu, Mobilim: Mobile Learning Management Framework System for Engineering Education, *International Journal of Engineering Education*, **24**(1), 2008, pp. 32–39.
12. M. Milrad and M. H. Jackson, Designing and Implementing Educational Mobile Services in University Classrooms Using Smart Phones and Cellular Networks, *International Journal of Engineering Education*, **24**(1), 2008, pp. 84–91.
13. W. H. Wu, J. Y. C. Wu, C. Y. Chen, H. Y. Kao, C. H. Lin and S. H. Huang, Review of trends from mobile learning studies: A meta-analysis, *Computers & Education*, **59**(2), 2012, pp. 817–827.
14. V. Venkatesh, M. G. Morris, G. B. Davis and F. Davis, User acceptance of information technology: Toward a unified view, *MIS Quarterly*, **27**(3), 2003, pp. 425–478.
15. E. T. Straub, Understanding technology adoption: Theory and future directions for informal learning, *Review of Educational Research*, **79**(2), 2009, pp. 625–649.
16. P. J. Li and R. Kishore, How robust is the UTAUT instrument? A multigroup invariance analysis in the context of acceptance and use of online community weblog systems, *Proceedings of the Conference on Computer Personnel Research,* New York, 2006, pp. 183–189.
17. V. Venkatesh, M. G. Morris and P. L. Ackerman, A longitudinal field investigation of gender differences in individual technology adoption decision making processes, *Organizational Behaviour and Human Decision Processes*, **83**(1), 2000, pp. 33–60.
18. N. Mallat, R. Matti, V. K. Tuunainen and A. Oorni, An empirical investigation of mobile ticketing service adoption in public transportation, *Personal and Ubiquitous Computing*, **12**(1), 2008, pp. 57–65.
19. C. Carlsson, J. Carlsson, K. Hyvonen, J. Puhakainen and P. Walden, Adoption of mobile devices/services—searching for answers with the UTAUT, *Proceedings of the 39th Annual Hawaii International Conference on System Sciences,* Kauia, HI, 2006, p. 132a.
20. M. G. Morris and V. Venkatesh, Age differences in technology adoption decisions: Implications for a changing workforce, *Personnel Psychology*, **53**(2), 2000, pp. 375–403.
21. V. Venkatesh, Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model, *Information Systems Research*, **11**(4), 2000, pp. 342–365.
22. Predictors of engagement and participation in an on-line course, http://www.westga.edu/~distance/ojdla/spring61/miller61.htm, Accessed June 30, 2013.
23. D. Shen, J. Laffey, Y. Lin and X. Huang, Social influence for perceived usefulness and ease-of-use of course delivery systems, *Journal of Interactive Online Learning*, **5**(3), 2006, pp. 271–282.
24. Y. S. Wang and Y. W. Shih, Why do people use information kiosks? A validation of the unified theory of acceptance and use of technology, *Government Information Quarterly*, **26**(1), 2008, pp. 158–165.
25. F. Concannon, A. Flynn and M. Compbell, What campus-based students think about the quality and benefits of e-learning?, *British Journal of Educational Technology*, **36**(3), 2005, pp. 501–512.
26. D. Schunk, D, *Learning theories: An educational perspective*, Pearson Education, Upper Saddle Hill, NJ, 2008.
27. Literature review in mobile technology and learning (Futurelab Report 11), http://archive.futurelab.org.uk/resources/documents/lit_reviews/Mobile_Review.pdf, Accessed June 30, 2013.
28. B. Kaigin and N. Basoglu, Adoption factors of mobile services, *Proceedings of the International Conference on Mobile Business*, Copenhagen, Denmark, 2006, p. 41.
29. W. T. Wang and M. Li, Factors influencing mobile services adoption: A brand-equity perspective, *Internet Research*, **22**(2), 2012, pp. 142–179.
30. R. Daft and R. Lengel, Organizational informational requirements, media richness and structural design, *Management Science*, **32**(5), 1986, pp. 554–571.
31. E. Huizingh, The content and design of web sites: An empirical study, *Information Management*, **37**(3), 2000, pp. 123–134.
32. J. S. Eccles, Expectancies, values, and academic behaviour, in J. Spence (ed.), *Achievement and achievement motivation,* W.H. Freeman and Company, San Francisco, CA, 1983, pp. 75–146.
33. J. S. Eccles and A. Wigfield, Expectancy-value theory of achievement motivation, *Contemporary Educational Psychology*, **25**(1), 2000, pp. 68–81.
34. C. M. Chiu and E. T. G. Wang, Understanding web-based learning continuance intention: The role of subjective task value, *Information & Management*, **45**(3), 2008, pp. 194–201.
35. P. Smith, K. Murphy and S. Mahoney, Towards identifying factors underlying readiness for online learning: An exploratory study, *Distance Education*, **24**(1), 2003, pp. 57–67.
36. M. Sharpe, Disruptive devices: Mobile technology for conversational learning, *International Journal of Continuing Engineering Education and Lifelong Learning*, **12**(5/6), 2003, pp. 504–520.
37. W. Li, Virtual knowledge sharing in a cross-cultural context, *Journal of Knowledge Management*, **14**(1), 2010, pp. 38–50.
38. Mobile learning: Research findings (Report to Becta), http://www.lopendleren.nl/documenten/achtergrondinformatie/Becta_mobile-learning-july07.pdf, Accessed September 10, 2012.
39. Y. S. Wang, M. C. Wu and H. Y. Wang, Investigating the determinants and age and gender differences in the acceptance of mobile learning, *British Journal of Educational Technology*, **40**(1), 2009, pp. 92–118.
40. J. Moon and Y. Kim, Extending the tam for a world-wide-web context, *Information and Management*, **38**(4), 2001, pp. 217–230.
41. J. H. Huang and Y. R. Lin, Elucidating user behaviour of mobile learning: A perspective of the extended technology acceptance model, *The Electronic Library*, **25**(5), 2007, pp. 585–598.
42. J. Lattin, J. D. Carroll and P. E. Green, *Analyzing multivariate data*, Thomson Brooks/COLE, Belmont, CA, 2003.
43. D. Gefen, D. W. Straub and M. Boudreau, Structural equation modelling and regression: Guidelines for research practice, *Communications of the Association for Information Systems*, **4**(7), 2000, pp. 1–78.
44. D. Campbell and D. Fiske, Convergent and discriminant validation by the multitrait-multimethod matrix, *Psychological Bulletin*, **56**(2), 1959, pp. 81–105.
45. L. Hu and P. Bentler, Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, *Structural Equation Modelling*, **6**(1), 1999, pp. 1–55.
46. P. M. Bentler and D. G. Bonnet, Significance tests and goodness of fit in the analysis of covariance structures, *Psychological Bulletin*, **88**(3), 1980, pp. 588–606.

Appendix A

Table A.1 Survey items used in the study

No.	Items	Standardized Factor loadings
PE1	I would find using m-Learning would improve my academic life performance.	0.876
PE2	I would find using m-Learning would enhance effectiveness of my learning (do things better and smarter).	0.848
PE3	I would find using m-Learning would increase my chances of getting a better grade.	0.807
PE4	I would find using m-Learning is useful for my learning process.	0.783
EE1	I would find learning how to use m-Learning is easy for me.	0.785
EE2	I would find my interaction with m-Learning is clear and understandable to me.	0.838
EE3	I would find it is easy for me to become skillful to use m-Learning.	0.839
EE4	I would find m-Learning is easy to use	0.763
	If I had a mobile device and I would use it for completing a learning activity,	
SE1	If I had a built-in help facility for assistance.	0.770
SE2	If someone had showed me how to do it first.	0.704
PEn1	I would find using m-Learning would lead to my exploration.	0.794
PEn2	I would find using m-Learning would stimulate my curiosity.	0.795
PEn3	I would find using m-Learning to solve problems would be appealing to me.	0.836
SI1	I would use m-Learning if my professor has referred the importance and effectiveness of using it.	0.761
SI2	I would use m-Learning if my professor has advocated using it.	0.905
FC1	I would use m-Learning if my university provides good technical support.	0.840
FC2	I would use m-Learning if my university provides me instruction, training, and assistance when needed.	0.866
SML1	I would find using m-Learning provides me more flexibility in controlling my learning process and choosing what I want to learn.	0.747
SML2	I would find using m-Learning helps me set aside reading and homework time.	0.879
SML3	I would find using m-Learning helps me in managing study time and schedules effectively and complete assignment on time	0.812
Ubi1	I would find using m-Learning increases my access to learning resources.	0.784
Ubi2	I would find having course materials, such as slides, lecture notes, and practice quizzes, available on the mobile devices is convenient to me.	0.754
AV1	I would feel a sense of ownership if using m-Learning.	0.921
AV2	I would find using m-Learning is helpful in achieving learning goals.	0.927
BI1	I would recommend others to use m-Learning.	0.814
BI2	I intend to use m-Learning more frequently.	0.816
BI3	I would enjoy using m-Learning.	0.887
BI4	I intend to use m-Learning in my academic life.	0.803
SQ1	It is important for the content to be up-to-date and accurate.	0.821
SQ2	It is important for the content to be understandable.	0.784
SQ3	It is important to have content easy to navigate.	0.919
SQ4	It is important to have a user-friendly interface.	0.874

Yu Huang, PhD, attended the Wuhan University in China and obtained a Bachelor of Engineering degree in printing technology in 2006. After graduation, she headed to the University of Wisconsin-Stout where she received a Master of Science degree in human resources development. Later on, she studied Industrial and Systems Engineering in University of Tennessee, Knoxville and received PhD degree in 2014. Her research interests include operations research and mobile learning.

Xueping Li, PhD is an Associate Professor in the Department of Industrial and Systems Engineering, the Director of the Ideation Laboratory (iLab), and Co-Director of the Health Information Technology and Simulation (HITS) Lab at the University of Tennessee - Knoxville. He holds a Ph.D. from Arizona State University. His research areas include complex systems modeling, simulation, optimization; scheduling; engineering education; and supply chain logistics. He is a member of IIE, ASEE, IEEE and INFORMS.

Mehmet Aydeniz, PhD, is an Associate Professor of Science Education at The University of Tennessee, Knoxville. He received his M.S. with a concentration in chemistry in 2001, and his Ph.D. in 2007 from The Florida State University in Science Education. His scholarship focuses on teacher learning, teacher change and science teacher effectiveness in the area of inquiry, argumentation, and modeling. His research program on student learning focuses on assessment of students' learning, engineering education, and computational thinking.

Tami H. Wyatt, PhD, is Director of Graduate Studies, College of Nursing, and Co-Director of the Health Information Technology and Simulation Lab at the University of Tennessee Knoxville. She obtained a bachelor's degree from Radford University, two master's degrees: one in critical care nursing and another in instructional technology and a doctorate in research from the University of Virginia. Dr. Wyatt's focus on teaching and instructional technology has resulted in awards from the National League for Nursing, American Association of Colleges of Nursing, Sigma Theta Tau National Honor

Society, Glaxo Smith Kline, Tennessee Nurses Association, and the University of Tennessee Research Foundation. In 2012, Dr. Wyatt was selected as a Harvard Macy Scholar, one of only a few nurses in the interprofessional program. In 2013, Dr. Wyatt was selected to participate in the NIH funded mHealth Summer Training Institute and in 2014; she was named a fellow in the American Academy of Nursing and in the Robert Wood Johnson Executive Nurse program.